Capstone Project Phase A

# AutoScope – Moblie application for ear infection detection

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GitHub: https://github.com/ndvp39/autoscope

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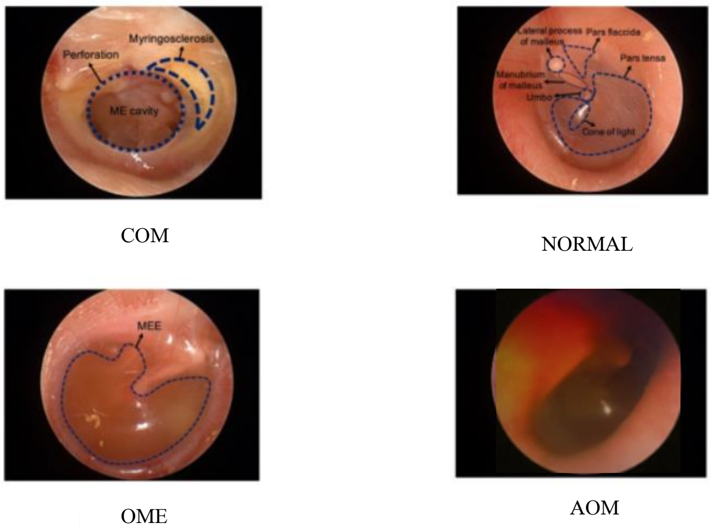
# Abstract

Ear infections are a common health issue, especially among children, and early detection is crucial for effective treatment and management. This project aims to develop an innovative solution by integrating a digital otoscope with a mobile application to detect early signs of ear infections. Utilizing advanced image processing and machine learning techniques, the project employs ResNet50, InceptionResNetV2, and VGG16 architectures from Keras applications, initialized with ImageNet weights, to analyze images captured by the otoscope. The mobile application offers a user-friendly interface for capturing and assessing ear images, providing healthcare professionals with a reliable tool for rapid and accurate diagnosis. By enabling precise detection, this solution aims to reduce unnecessary use of antibiotics, thus helping to combat antibiotic resistance and promoting more targeted treatment strategies. The overall goal is to enhance the accessibility and efficiency of ear infection diagnosis, improving patient outcomes and reducing the need for in-person consultations.

# 1. Introduction

Ear infections (Otitis media) are a prevalent concern, especially among young children. These infections, if not detected and treated early, can lead to complications, prolonged discomfort, and the overuse of antibiotics [5]. The excessive use of antibiotics contributes to the growing issue of antibiotic resistance, a significant public health threat [5]. Timely detection and treatment of ear infections can reduce the need for systemic antibiotics, favoring localized treatments such as ear drops, which are less likely to contribute to resistance [5].
Otitis media (OM), refers to an illness usually found in children under the age of three years [4]. In the U.S., the medical expenses of ear infections are predicted to be $ 3 to 5 billion annually [9]. Three kinds of OM exist: chronic otitis media with effusion, acute otitis media (AOM), and otitis media with effusion (OME). Due to bacterial infection, AOM may occur in the middle of the ear, bringing about the build-up of fluid. OME leads to fluid build-up in the middle of the ear because of inflammation, which is much more severe than AOM [5].




Source: Automatic detection of tympanic membrane and middle ear infection from oto-endoscopic images via convolutional neural networks, 2020.
Intelligent Control Techniques for the Detection of Biomedical Ear Infection, 2022

Figure1: Sample images of different ear infection classes

Current solutions for diagnosing ear infections rely heavily on clinical examinations conducted by healthcare professionals using an otoscope. These examinations, though effective, are often limited by accessibility, requiring patients to visit clinics or hospitals. By the time the patient is examined, the ear infection can be worsened.
In some cases, diagnostic accuracy can be affected by the practitioner's experience and the subjective nature of visual assessments. There are also digital otoscopes available that can capture images of the ear canal, but they typically lack integrated diagnostic capabilities and require manual interpretation by a medical professional.
Our project aims to develop an innovative solution combining a digital otoscope with a mobile application that utilizes advanced image processing techniques to detect early signs of ear infections. The digital otoscope will capture high-quality images of the ear canal and eardrum, which will then be analyzed by our application. The app will leverage machine learning algorithms trained on a vast dataset of ear images to identify potential infections with high accuracy.

Our project integrates advanced deep learning algorithms to analyze the images captured by the digital otoscope. By utilizing models such as ResNet50, InceptionResNetV2, and VGG16, we ensure accurate and efficient detection of early signs of ear infections. These algorithms are specifically chosen for their ability to extract fine-grained details from medical images, identify key patterns related to infections, and classify them with high precision. This combination of models allows our application to detect subtle variations in eardrum conditions, enabling prompt and reliable diagnoses.
Our solution will provide a reliable, accessible, and user-friendly method for early detection of ear infections, potentially reduce the dependency on antibiotics by enabling prompt treatment with ear drops and the need for clinical visits.

The primary beneficiaries of our solution are young children and their parents. Children are particularly vulnerable to ear infections, and early detection can prevent severe discomfort and complications. Parents will benefit from the convenience of monitoring their child's ear health from home, reducing the frequency of doctor visits and the associated costs and time.
Healthcare providers will also find value in our solution. It can serve as a decision-support tool, assisting them in making accurate diagnoses more quickly and efficiently. This can lead to better patient outcomes and optimized use of medical resources.
Moreover, public health systems stand to gain from a reduction in antibiotic prescriptions. By minimizing unnecessary antibiotic use, our solution can contribute to the broader effort of combating antibiotic resistance, ultimately benefiting society.

# 2. Background and Related Work

This chapter provides a comprehensive review of the current tools and methods used for diagnosing ear infections, highlighting their advantages and limitations. It also examines the existing literature on the application of advanced image processing and machine learning techniques in medical diagnostics, specifically within the context of otolaryngology. By exploring the strengths and gaps in current solutions, this survey underscores the necessity for our proposed approach, which aims to enhance early detection of ear infections and reduce the reliance on antibiotics.

## 2.1 Existing Tools

### 2.1.1 Traditional Otoscope

The traditional otoscope is a handheld device extensively utilized by healthcare professionals to examine the ear canal and eardrum. It consists of a light source and a magnifying lens, enabling visual inspection of the ear's internal structures.
The effectiveness of a traditional otoscope is contingent upon the practitioner's expertise and experience. Additionally, the requirement for patients to visit a healthcare facility for examination limits accessibility and convenience. This tool also lacks any automated diagnostic features, relying solely on the clinician's interpretation.

### 2.1.2 Telemedicine Solutions

Telemedicine platforms (for example TytoCare [1]) leverage digital communication technologies to facilitate remote consultations between patients and healthcare professionals. These platforms often incorporate digital otoscopes to enable remote examination of the ear.

The efficacy of telemedicine solutions is dependent on the availability and promptness of healthcare professionals to interpret the received images. This can result in potential delays in diagnosis and treatment. Additionally, these platforms often do not incorporate automated diagnostic tools, thus relying on human expertise.

### 2.1.3 Mobile Applications for Digital Otoscope

Digital otoscopes (Oto by CellScope [2]) are advanced versions of traditional devices capable of capturing high-resolution images and videos of the ear canal and eardrum. These devices can integrate with mobile applications (HearScope [3]) designed to assist users in managing ear health by providing educational resources, symptom checkers, and enabling image capture for remote analysis.

Despite their ability to capture detailed images and offer some guidance, these tools generally lack sophisticated diagnostic capabilities. They still require manual interpretation by healthcare professionals or rely on basic algorithms, limiting their reliability and diagnostic accuracy compared to professional evaluations.

## 2.2 Literature Review

### 2.2.1 Advantages of Early Detection of Ear Infections

The early detection of ear infections is crucial for preventing a range of complications that can arise if these infections are not promptly treated. Complications from untreated ear infections include hearing loss, tympanic membrane perforation, and the spread of infection to nearby structures such as the mastoid bone, which can lead to mastoiditis [4]. By identifying infections at an early stage, appropriate treatments such as ear drops can be administered, which are less invasive and carry fewer side effects compared to systemic antibiotics [5].

Additionally, the overuse of systemic antibiotics for treating ear infections has contributed significantly to the global issue of antibiotic resistance. Antibiotic resistance occurs when bacteria evolve mechanisms to withstand the drugs used to treat infections, rendering standard treatments ineffective and leading to persistent infections [6]. By reducing the reliance on systemic antibiotics through early detection and localized treatment options, the progression of antibiotic resistance can be mitigated, preserving the efficacy of these critical medications for future use [7].

The importance of early diagnosis is further highlighted by studies that demonstrate improved patient outcomes when ear infections are treated promptly. Early intervention has been shown to reduce the duration of symptoms, lower the incidence of recurrent infections, and decrease the overall burden on healthcare systems [8]. Moreover, timely treatment helps in avoiding unnecessary healthcare visits and reduces the economic strain associated with long-term complications and treatments [9].

### 2.2.2 Machine Learning for Medical Image Analysis

A considerable body of scholarly work underscores the efficacy of machine learning algorithms in the realm of medical image analysis. Techniques such as convolutional neural networks (CNNs) have demonstrated significant accuracy in various image classification and diagnostic tasks [10]. For instance, recent studies elucidate the transformative potential of deep learning in healthcare, particularly emphasizing improvements in diagnostic precision [10]. Furthermore, comprehensive reviews of deep learning methodologies applied to medical imaging highlight their capacity to enhance diagnostic processes significantly [11].

### 2.2.3 Applications of Ear Images Processing

To ensure reliable spectral data classification, several key preprocessing steps must be executed on multimode image data. Initially, all RGB images, except for white light and fluorescence images, are converted to grayscale. This is followed by flat-field correction to normalize the images. Misalignments caused by hand movements during image acquisition intervals are corrected through image registration. For autofluorescence images, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm is applied to enhance contrast, and then image registration is performed again. The preprocessed images are then stacked into a multimode image cube consisting of nine grayscale spectral images and the red (R), green (G), and blue (B) channels of the autofluorescence image. The performance of various data combinations from this multimode image cube is compared to identify the best data set for classifying ear infections, specifically Otitis Media with Effusion (OME), Acute Otitis Media (AOM), and Chronic Otitis Media (COM) [12].

To classify ear images, various machine learning and conventional spectral classification algorithms are applied, including Multilayer Perceptron (MP), Random Forest (RF), Logistic Regression (LR), Decision Trees (DTs), Naive Bayes (NB), Spectral Angle Mapper (SAM), and Euclidean Distance (ED). These algorithms have been widely used in spectral imagery data analysis [13, 14]. For training and testing, ground truth data is established with medical experts identifying specific regions for each class (OME, AOM, and COM). Binary masks are created and applied to the image cube, followed by data standardization to account for varying intensity levels across different channels. The dataset is then split into 80% for training and 20% for testing.

MP is used to classify multimode images with an input layer of 12 nodes (representing nine spectral images and the R, G, and B channels of one autofluorescence image), a hidden layer optimized to ten nodes, and an output layer of three nodes (OME, AOM, and COM). The performance of the MP model is compared to other classifiers, with parameters tuned for optimal results. For instance, the RF classifier designed for multimode data uses 58 estimators, a maximum tree depth of 10, and specific minimum samples split and leaf parameters. Similar detailed configurations are used for DTs and other classifiers to achieve the highest classification accuracy [13, 15, 16].

Other machine learning classifiers, including LR and NB, are also tested on various data combinations. For example, the RF classifier for multimode data is fine-tuned with 24 estimators and specific tree depths and minimum samples parameters, while the DT classifier is optimized similarly. The criteria for split quality measure is entropy, ensuring precise classification. Each classifier's performance is rigorously evaluated to determine the most effective algorithm for each data type, thereby ensuring robust and accurate classification of OME, AOM, and COM from multimode images [13, 14].

# 3. Expected Achievements

The primary goal of our project is to develop a comprehensive, user-friendly mobile application integrated with an otoscope for the early detection of ear infections. This project will result in several key achievements:

## 3.1 Mobile Application Development

We will create a mobile application capable of capturing otoscopic images, performing real-time image processing, and providing diagnostic results. The app will feature an intuitive user interface designed for ease of use by both healthcare professionals and non-specialists.

## 3.2 Image Processing and Analysis

The core of our system will be an advanced image processing algorithm leveraging machine learning techniques. This algorithm will analyze images captured by the otoscope to detect signs of Otitis Media with Effusion (OME), Acute Otitis Media (AOM), and Chronic Otitis Media (COM). The system will utilize preprocessing steps, including image conversion, flat-field correction, image registration, and contrast enhancement, to prepare images for accurate analysis.

## 3.3 Machine Learning Model

Our machine learning model will be trained on a large dataset of labeled otoscopic images. We will compare various classification algorithms, such as Multilayer Perceptron (MP), Random Forest (RF), Logistic Regression (LR), Decision Trees (DTs), and Naive Bayes (NB), to determine the most effective approach for our needs. The model will be optimized to achieve high accuracy in classifying ear infections, leveraging spectral and autofluorescence image data.

## 3.4 User Education and Support

The app will include educational resources to help users understand ear infections and the importance of early detection. Additionally, support features will be implemented to guide users through the process of capturing images and interpreting results.

The success of our project will be evaluated based on the following criteria:

## 3.5 Accuracy and Speed of Detection

The primary success metric will be the accuracy and speed of the image processing and machine learning model in detecting OME, AOM, and COM. We aim for an accuracy rate of over 90%, as validated by comparison with diagnoses made by medical professionals. Additionally, the detection process should be fast enough to provide real-time or near-real-time results, ensuring prompt diagnosis and treatment.

## 3.6 User Interface and Experience

The application’s user interface must be intuitive and user-friendly, enabling easy image capture and result interpretation. User feedback and usability testing will be conducted to ensure a positive user experience.

## 3.7 Integration with Otoscope

Successful integration of the otoscope with the mobile application is crucial. The system must reliably capture high-quality images and process them efficiently.

### 3.8 Reduction in Antibiotic Usage

One of our key goals is to reduce the reliance on antibiotics for ear infections. Success in this area will be assessed through follow-up studies evaluating the impact of early detection on treatment choices and outcomes.

# 4. Engineering Process

## 4.1 Process Description and Explanation

### 4.1.1 Motivation and Rationale

The primary motivation for developing a solution to detect early signs of ear infections stems from the significant impact such infections can have on individuals, especially children. Early detection can prevent severe complications, reduce the need for invasive treatments, and mitigate the growing issue of antibiotic resistance. By leveraging advanced image processing and machine learning, we aim to create a reliable, non-invasive method for early diagnosis, which can be conveniently used in clinical settings or at home.

### 4.1.2 Current Development Process

**Dataset**

First, we will focus on data collection by searching for reliable online medical databases and publicly available datasets to gather a diverse set of ear images, including conditions such as Otitis Media with Effusion, Acute Otitis Media, and Chronic Otitis Media. If suitable datasets are not found, we will initiate collaborations by reaching out to hospitals and healthcare institutions to obtain annotated images. This combined approach will ensure a large, well-labeled dataset of both healthy and infected cases, which will be used to train robust machine learning models.

**Application and Otoscope**

The next step is to integrate the trained machine learning model with a digital otoscope for real-time image capture and analysis. This involves developing an interface between the otoscope and the mobile application, ensuring seamless data transfer and real-time processing. The goal is to have an integrated solution where the otoscope captures ear images, and the mobile application analyzes them using the trained model.

The mobile application will be designed to be user-friendly for both patients and healthcare providers. It will include image processing and classification functionalities, as well as features for storing and sharing results. This will make the application fully functional and available on major platforms (iOS and Android).

Field testing and feedback collection will then be conducted to test the integrated solution in real-world settings. Feedback from healthcare providers and patients will be collected to make necessary adjustments based on user experience, ensuring the solution is improved based on real-world usage and feedback.

## 4.2 Future Development Process

Moving forward, we plan to enhance the system based on the feedback from the initial field testing. This includes refining the user interface, improving image processing algorithms, and ensuring the seamless functionality of the otoscope and mobile application.

Additionally, we aim to integrate advanced features such as remote consultations, where users can send images and results to healthcare professionals for further review by sharing the results. This will add an extra layer of assurance for users, ensuring they receive expert advice when necessary.

## 4.3 Various Constraints Affecting the Development Process

### 4.3.1 Obtaining a Sufficient Dataset

One of the significant challenges in our development process is acquiring a comprehensive and diverse dataset of ear images. The dataset needs to be large enough to include various conditions such as Otitis Media with Effusion, Acute Otitis Media, and Chronic Otitis Media, as well as images of healthy ears. This diversity is crucial for training robust and accurate machine learning models.

Mitigation Strategies:

Collaborating with Healthcare Institutions: Establish partnerships with clinics, hospitals, and research institutions to gain access to annotated medical images.

Utilizing Online Medical Databases: Source images from publicly available medical databases and academic resources. Many medical research databases offer datasets for research purposes.

### 4.3.2 Ensuring the Accuracy and Reliability of the Otoscope

Another significant challenge is ensuring that the otoscope captures high-quality images that can be accurately analyzed by the machine learning model. Variations in lighting, hand movements, and the positioning of the otoscope can affect image quality and, consequently, the diagnostic accuracy.

Mitigation Strategies:

Standardized Usage Guidelines: Develop clear, user-friendly instructions and training materials for using the otoscope. This includes guidance on positioning, lighting, and handling to ensure consistent image quality.

Real-Time Feedback Mechanism: Implement a real-time feedback system within the app to guide users in capturing optimal images. For example, the app can indicate if the image is too dark or if the otoscope is not positioned correctly.

Image Preprocessing Algorithms: Incorporate advanced image preprocessing techniques, such as flat-field correction, contrast enhancement, and image stabilization, to improve the quality of captured images before analysis.

### 4.3.3 Communicating the Non-Clinical Nature of the App

Since the application is not a substitute for a professional medical diagnosis, it is crucial to clearly communicate this to users. Users should be aware that the app provides a preliminary analysis and that they should consult a healthcare professional for an official diagnosis.

Mitigation Strategies:

Clear Messaging: Include prominent disclaimers within the app and on all related documentation, stating that the app is intended for preliminary analysis and should not replace a doctor's evaluation.

User Education: Provide educational resources within the app to inform users about the importance of seeking professional medical advice. This can include information on recognizing symptoms that require immediate medical attention.

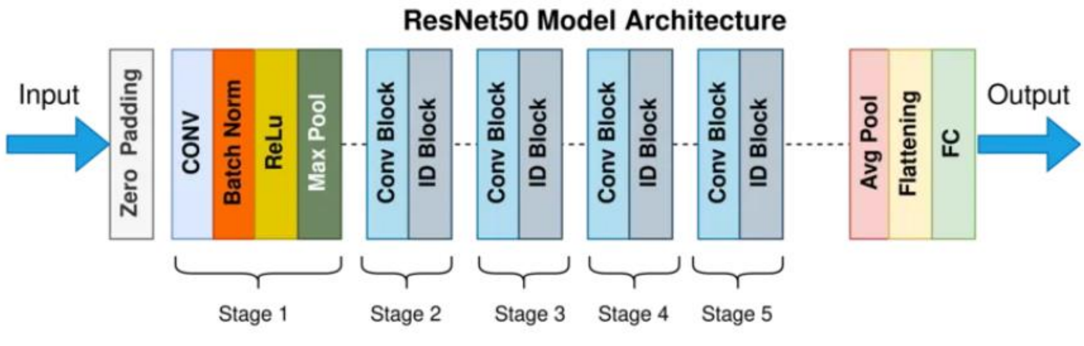
Notification System: Implement a notification system that reminds users to consult a healthcare provider, especially if the app detects signs of an infection. This can include automated messages or alerts emphasizing the importance of professional consultation.

By addressing these constraints and implementing the suggested mitigation strategies, we aim to develop a reliable and effective solution for the early detection of ear infections.

## 4.2 Product Description

### 4.2.1 Description of Algorithms Used

**ResNet50:**




ResNet50 Architecture

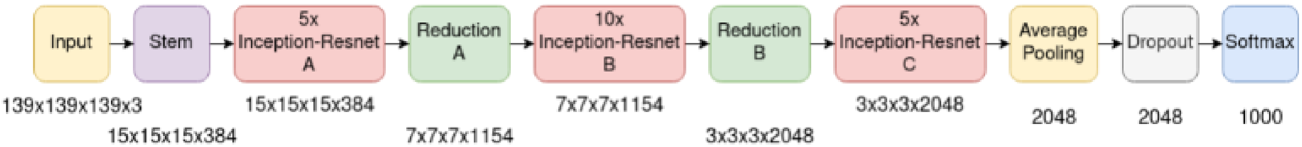
ResNet50 is a deep convolutional neural network consisting of 50 layers. It is designed to efficiently extract and process features from input images, such as those of an eardrum, by passing through various stages including convolutional layers, identity blocks, and convolutional blocks. A key innovation in ResNet50 is the use of "skip connections," which help solve the vanishing gradient problem, allowing the network to maintain strong performance even at great depth. These connections enable the network to learn more complex patterns without losing accuracy, making ResNet50 particularly effective for tasks like medical image analysis.

**Convolutional Block (Conv Block):** This block is responsible for down-sampling the image dimensions while increasing the depth of the feature maps. It's crucial in identifying complex patterns like signs of infection in different regions of the eardrum.

**Identity Blocks (ID Block):** These blocks pass the input through without altering the dimensions but allow the network to focus on refining features extracted in earlier layers. This helps in detecting fine details that might indicate the presence of an ear infection.

In the context of ear infection detection, ResNet50 processes the eardrum image through these stages to identify subtle patterns and features that correlate with different types of infections.

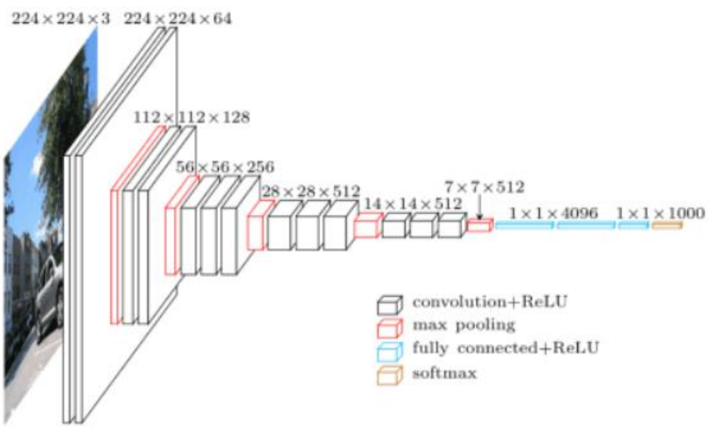
**InceptionResNetV2:**



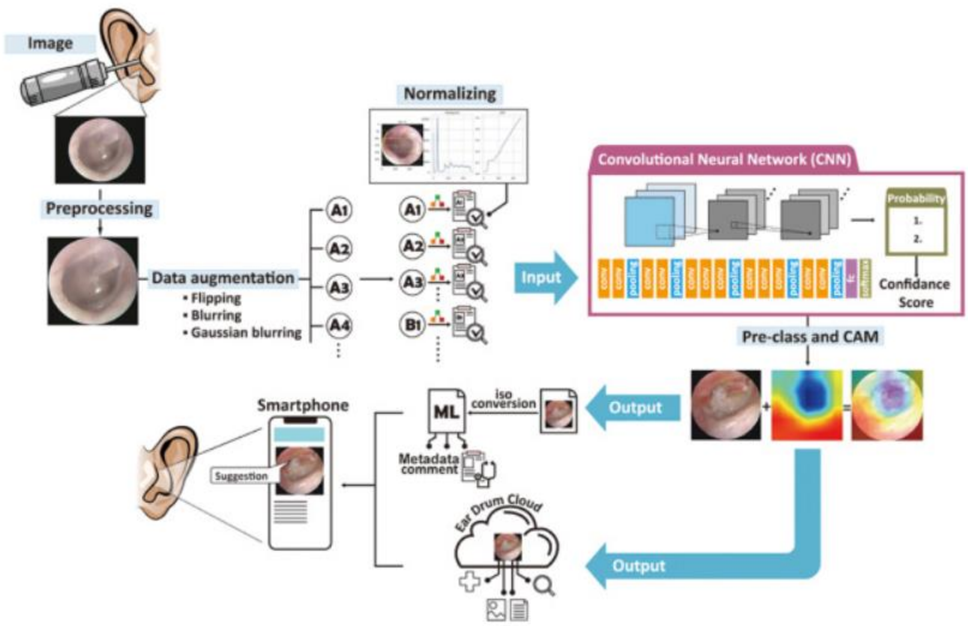

InceptionResNetV2 is a deep convolutional neural network that combines the ideas from the Inception architecture with residual connections from ResNet. The architecture is designed to be very deep and efficient in terms of both computation and memory usage. It uses inception blocks that allow the network to extract features at multiple scales simultaneously. These blocks are combined with residual connections, which help prevent the vanishing gradient problem, allowing the network to be trained more effectively.

In the context of ear infection detection, InceptionResNetV2 processes input images of the eardrum through its series of inception-residual blocks, progressively learning complex features that are critical for distinguishing between healthy and infected eardrums.

**VGG16:**



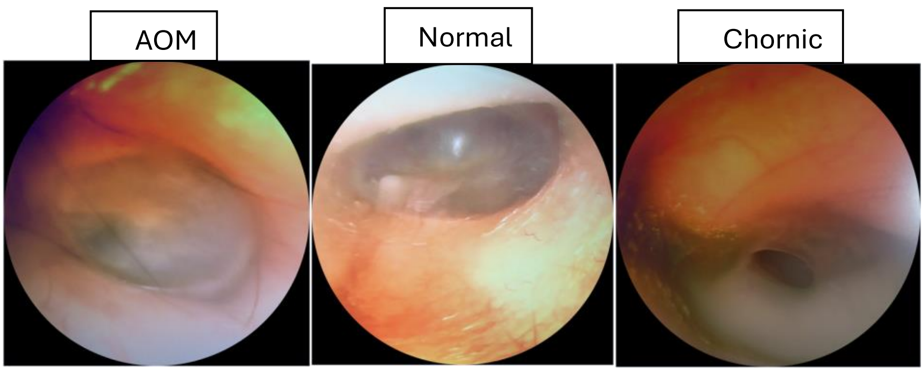
VGG16 is characterized by its simplicity and uniform structure, using a stack of convolutional layers with small receptive fields (3x3). The network processes an input image, such as an otoscopic image of an eardrum, through these convolutional layers to extract important features like edges and textures. These features are then down-sampled using max pooling layers to reduce the spatial dimensions, making the process more efficient. Afterward, the feature maps are flattened and passed through fully connected layers that contribute to high-level decision-making. Finally, the output is classified using a softmax layer, which assigns probabilities to different ear conditions, aiding in the detection of issues like ear infections.




## 4.2.2 Description of the Dataset

The dataset consists of images of ears, labeled with conditions such as "normal" or other cases. Each image is annotated to indicate the presence or absence of infection-related features.

Example of the dataset:



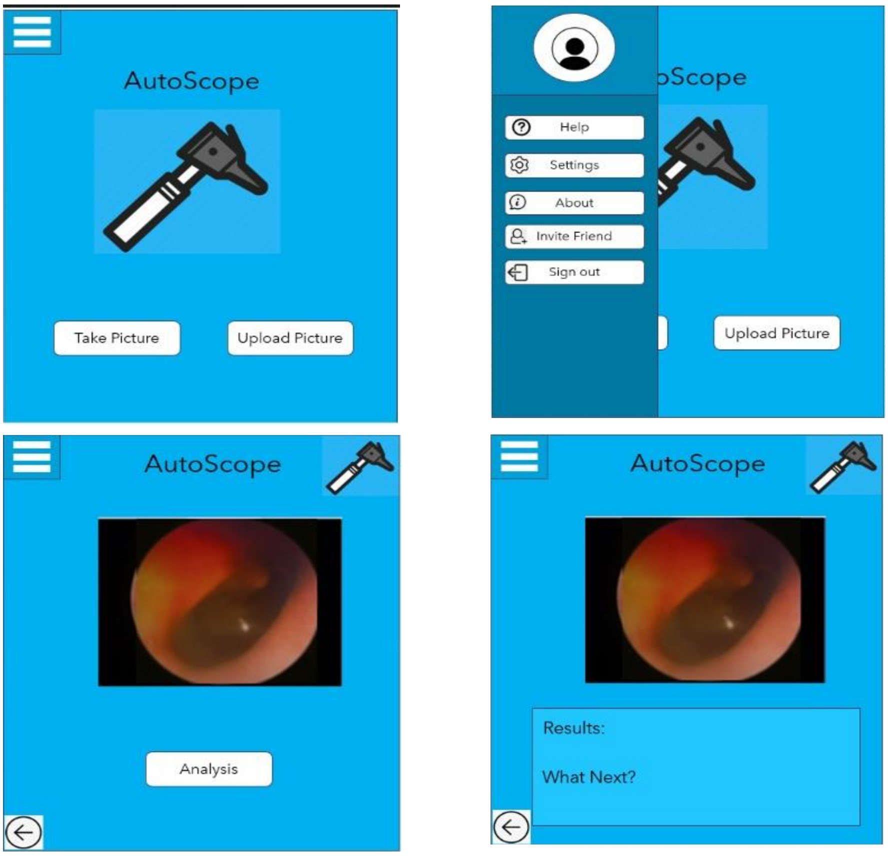

(DataSet: https://www.kaggle.com/datasets/erdalbasaran/eardrum-dataset-otitis-media)

### 4.2.3 User Interface Description

- **Home Screen**:
  - **Upload Button**: Allows users to upload ear images for analysis.
  - **Take Picture**: Allows users to take a picture using the otoscope for analysis.

- **Analysis Screen**:
  - **Image Display**: Shows the uploaded ear image along with diagnostic results.
  - **Results**: Displays the classification result (e.g., "Normal" or other cases) with a confidence score.

- **Additional Features**:
  - **History**: Users can view previous analyses and results.
  - **Feedback**: Option for users to provide feedback on the results or the app's performance.
  - **Support**: Provides access to help or contact information for technical support.
  - **Help**: Provides brief guidance on how to use the app and upload images.
  - **About**: Options to access additional information about the app and its functionality.




The UI should be intuitive, easy to navigate, and designed to provide clear and actionable insights based on the model's analysis of ear images.

# 5. Evaluation Verification Plan

To evaluate and verify the ear infection detection model, we start by defining clear objectives and performance metrics, then collect, label, and split the data into training, validation, and test sets. During model training, we use the validation set to tune hyperparameters and prevent overfitting. After training, we evaluate the model using the test set, calculating metrics like accuracy and recall, and generating a confusion matrix. We perform cross-validation and external validation to ensure generalizability, followed by expert review for additional verification. Regular monitoring, error analysis, and updates ensure the model remains accurate and reliable over time, adapting to new data and maintaining its performance standards.

| **Objective** | **Test Methodology** | **Expected Outcome** | **Edge Cases** |
|---|---|---|---|
| Accuracy of Infection Detection | Test model using otoscope-connected phone app, analyze results with real-world images | Correct classification of infections with >80% accuracy | Blurry or obstructed images from device |
| Image Quality Assessment | Verify image quality from phone's camera under various lighting and ear conditions | Clear, usable images under most conditions | Poor lighting, low-resolution captures |
| Real-Time Processing | Measure time taken from image capture to infection detection | Response within seconds | Lag in app performance or network delay |
| Cross-Device Compatibility | Test functionality across multiple phone models and operating systems (iOS, Android) | Consistent performance on all devices | Incompatibility with certain devices |
| External Validation | Validate with real-world cases from hospitals and clinics | Accurate results, matching expert diagnosis | Variability in real-world ear conditions |
| Continuous Monitoring | Regularly analyze predictions, track errors, and update based on feedback | Continuous model improvement, maintain high accuracy | Degradation in performance with new data |
| Invalid Input | Testing case when user gives invalid input (not an eardrum image) | Displaying error message and requesting valid input | Valid input with low quality image |

# 6. Use of AI Tools

In this project, we mostly used Google Scholar search engine for our research, but we also used **ChatGPT**, an AI tool from OpenAI, to assist with research architecture, specifically for defining the structure and machine learning models that best suit the goals of the project.

**Prompt:**
*"What are the key considerations when designing the architecture of a machine learning system for medical image analysis?"*

To understand the foundational elements needed to design a robust machine learning architecture for medical image analysis, including aspects like model selection, data processing pipelines, computational requirements, and integration with mobile or cloud platforms.

**Prompt:**
*"What are the differences between ResNet50, InceptionResNetV2, and VGG16 in terms of suitability for medical image classification?"*

To understand the strengths and weaknesses of different neural network architectures for image classification tasks, particularly in medical fields.

**Prompt:**
*"What are the key challenges in detecting ear infections using machine learning and digital otoscope images?"*

To identify potential difficulties in image preprocessing, model training, and evaluation for ear infection detection, so that we could preemptively address these in the project.

**Prompt:**
*"Which metrics should be used to evaluate the performance of models like ResNet50, InceptionResNetV2, and VGG16 in medical imaging?"*

To determine the best metrics (e.g., accuracy, precision, recall, F1-score) for assessing the performance of the chosen models, ensuring reliable and clinically meaningful results.

By utilizing these AI-powered insights, we were able to solidify the research architecture, focusing on the most effective machine learning models, data preprocessing techniques, and evaluation strategies for the project.

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